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Further results on monopolistic competition, markup pricing and the business cycle in Switzerland

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Abstract This paper investigates how firms' market power affects the price level. Based on a small macro-model it is shown empirically that firms have structural markup pricing power and take advantage of favourable business cycle fluctuations. To this aim, a multivariate time series model with double integrated variables is estimated. Thereby a model-based business cycle indicator can be derived. Its information content is confronted with survey data giving rise to what is going to be called semantic cross validation approach.

Keywords Markup pricing · $I(2)$ cointegration analysis · Semantic cross validation · Business tendency surveys

1 Introduction

The Swiss economy is sometimes considered as an agglomeration of companies contending in a monopolistic competition. This is equivalent to saying that a considerable share of firms can pursue markup pricing where the markup is added to the marginal costs and depends on the elasticity of demand.

In this paper we extend the framework by suggesting that the stance of the business cycle may equip firms with additional or reduced pricing power, depending on whether the economy experiences a boom or a recession. In order to do so, a small, fairly standard partial macro-model is derived which describes price setting behaviour in the economy. It shows that the potency to set prices varies due to demand fluctuations and due to variations in technological progress. These variations can be estimated and it is shown that their impact on prices conforms with the theory. This leads to the conclusion that these estimated demand

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fluctuations can also be used as a business cycle indicator as it has been suggested by Granger and Jeon (2003). Owing to the origin of the indicator, it will be labelled economic filter in order to distinguish it from the technical approaches provided by among others the Hodrick–Prescott filter, the Beveridge–Nelson decomposition, structural time series analysis and so on.

The theoretical approach yields an implicit identification problem because pricing power (the markup) has two different sources. This paper addresses the identification issue by recurring to the large information set gathered in business tendency survey over the past decades. A demand pressure indicator is employed to check whether the empirical business cycle indicator can be attributed to demand shocks. It turns out that it does. While on the one hand this can be understood as support for the economic model, it can likewise be considered as a guideline for choosing survey data being particularly important for assessing the stance of the economy. This choice is independent of the particular semantic content of the survey data, yet depends on the observable effects on macro economic variables it can be associated with. This procedure is thus a two-ways issue and can hence be considered a semantic theory cross validation approach.

The work is motivated by the general search for a parsimoniously parametrised macroeconomic model for the Swiss economy of which this analysis is a building block. Previous attempts are mainly due to Stalder (1994, 1995) who also pointed out the advantages of survey data use. Banerjee et al. (2001, 2002) can be considered closely related studies where, however, specific labour cost data is used and Switzerland is not included in the country surveys.

The remainder of the paper is organised as follows. First, the theoretical model is briefly sketched, second, the data for the empirical application will be described and the empirical model will be set up. Then, the implied business cycle indicator is calculated and compared to a measure based on survey data. Finally, conclusions will be drawn.

2 The model economy and prices setting

The technology in the model economy is described by its principal input which is labour. Likewise, for simplicity, we assume that the cost of production is a function of labour input. With stable and low real interest rates this does seem to be an acceptable restriction.

We assume that the representative firm has some market power and can thus maximise income by equating marginal revenue and marginal costs. However, since revenues also depend on the demand for the output, the price firms can set will depend on demand and this will affect the choice of labour input.

Thus, the economy is described by

$$\begin{array}{lll} \text{production} & Q_t = Q(L_t), & \frac{\partial Q}{\partial L} > 0, \\ \text{costs} & C_t = C(Q(L_t)), & \frac{\partial C}{\partial L} = \frac{\partial C}{\partial Q}\frac{\partial Q}{\partial L}, \\ \text{demand} & P_t = P(Q(L_t)), & \frac{\partial P}{\partial L} = \frac{\partial P}{\partial Q}\frac{\partial Q}{\partial L}, \\ \text{demand elasticity} & \eta_t = \eta(P_t, Q_t), & \eta_t^{-1} = \frac{\partial P}{\partial Q}\frac{Q_t}{P_t} \text{ with } \eta_t < -1, \end{array}$$

where Q_t is the quantity of goods produced and sold at the market, L_t stands for labour input which is paid the wage W_t, and P_t is the price per unit of output. It is further assumed that the marginal costs of output are a function of wages and an exogenous factor, say τ_t, that represents mainly so-called labour augmenting technological progress and all other systematic components of the marginal costs for which more detailed information is not available. A workable specification is given by $\frac{\partial C}{\partial Q} = a_1 W_t^{a_2} \tau_t^{-a_3}$, $a_3 > 0$ and can be understood as some not too restrictive functional form. The assumption about a_3 should reflect the consideration that marginal costs decrease with technical progress. In some of the related literature, marginal costs enter the estimation procedure directly as unit labour costs. Unfortunately, for Switzerland this information is not available. Supposing, however, that wages are the most important marginal cost factor, this paper's approach can be considered equivalent to the approach taken, for example, by Banerjee et al. (2001) who cover exogenous factors such as technical progress by unit labour costs.

The firms maximise

$$\max_{L_t} P_t Q_t - C_t$$

and the first order condition can be given as

$$\frac{\partial Q}{\partial L}\left[\frac{\partial P}{\partial Q} Q_t + P_t\right] = \frac{\partial C}{\partial L}. \tag{1}$$

After expanding the first term in brackets, and substituting for the definitions given above we obtain

$$\begin{aligned} P_t\left(1+\eta_t^{-1}\right) &= a_1 W_t^{a_2} \tau_t^{-a_3} \\ P_t &= \left(1+\eta_t^{-1}\right)^{-1} a_1 W_t^{a_2} \tau_t^{-a_3}. \end{aligned} \tag{2}$$

According to Eq. 2 firms' markup over marginal costs is $(1+\eta_t^{-1})^{-1}$ and prices will principally be ruled by the evolution of wages. However, the literature knows various ways to link the markup also to inflation. One of them is the indirect relation via the so-called relative price variability (RPV) and the markup, for example. It claims that RPV is also a determinant of inflation. Such an argument has been put forth by Mankiw's (1985) 'menu cost' type model, or by Lach and Tsiddon's (1992) model which is in the Lucas' island model vicinity. The latter also provide empirical evidence as partly do Banerjee et al. (2002) who also give a more detailed account of the relevant literature.

Within the chosen approach, a link between inflation and markup can also be established. Key to understanding this relationship is the notion of profits being a nonlinear function of the demand elasticity which leads to nonlinear first and second partial derivatives.[1] In order to keep the exposition concise the details are referred to the Appendix. Here, it is simply noted that the empirical model should allow a role for inflation in the long-run equilibrium 2. To facilitate estimation it should be assumed that the shape of the demand curve is more or less stable while its position in the quantity-price space is subject to demand shocks. This implies to consider the possibility that firms do not always supply at the optimal point of the

[1] The nonlinearity is also preserved in the log-linear econometric version of the model.

demand curve. Occasionally this may result in too high or too low output relative to the optimal supply given by actual demand for goods which will be known only at a later stage.

This paper mimics previous investigations of the price-wage dynamics for countries like Australia, United States, United Kingdom, and other G7 countries like by e.g. Banerjee and Russell (2000), Banerjee et al. (2001, 2002). This paper also extends the existing literature in that it explicitly investigates the role of demand shocks for the price and wage setting. Bils (1987) and Banerjee et al. (2001), for example, assume also that demand shocks play a role in the short run, but they refrain from including a demand shock proxy in their econometric model that would enable them to assess the impact directly. If, however, demand shocks are excluded then any unexplained variation in P_t could be attributed to shocks to the markup without ever having the chance to distinguish between demand shocks and other disturbances. It will be shown below that unexpected variation in demand very likely plays a significant role for explaining the markup in Switzerland.

3 Empirical analysis

The theoretical model links wages, prices, income, labour productivity, inflation and demand elasticity. We use prices and wages as the endogenous variables, taking the logarithm of Eq. 2 and re-arranging, one can write

$$p_t - a_2 w_t - log(a_1) = \rho_t - \eta_t^* \tag{3}$$

where $\eta_t^* = log(1 + \eta_t^{-1})$, $\rho_t = log(\tau_t^{-a_3})$ and the convention applies that lower case letters indicate the logarithms of the variable defined in upper case letters. We may consider the following decomposition of the r.h.s. term of Eq. 3

$$\eta_t^* = b_0 + b_1 t + b_2 \varepsilon_{1,t} \tag{4}$$

$$\rho_t = c_0 + c_1 t + c_2 \varepsilon_{2,t} \tag{5}$$

where $\varepsilon_{i,t}$, $i=1, 2$ is a zero mean stochastic variable. Under the assumption that the shape of the demand curve remains constant, $b_1 = 0$ must hold and b_0 defines the log of the average markup. Furthermore, summing up η_t^* and ρ_t and defining $\delta_0 = b_0 - c_0 - \log(a_1)$, $\delta_1 = -c_1$, $\delta_2 = -a_2$, and $\varepsilon_t = c_2\varepsilon_{2,t} - b_2\varepsilon_{1,t}$ gives rise to the following estimable version of Eq. 2

$$p_t + \delta_2 w_t + \delta_1 t + \delta_0 = \varepsilon_t. \tag{6}$$

Since c_0 and a_1 are components of marginal costs, δ_0 does not identify the markup on marginal costs. Labelling $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ as demand and supply shocks, respectively, it is clear that ε_t cannot be attributed to either demand or supply shocks alone. It is noteworthy that Eq. 6 does not assign a role to inflation. It is

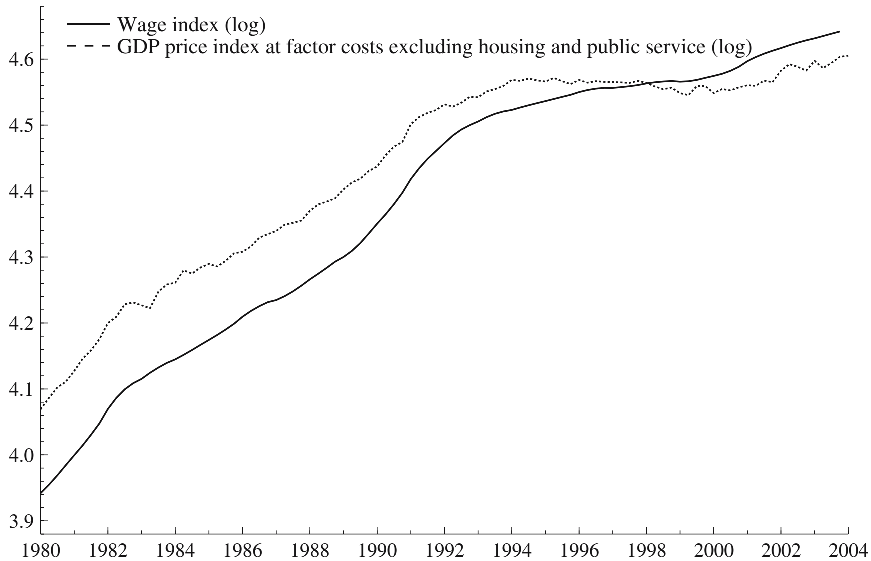

Fig. 1 Wage and price data (in logs)

shown in the Appendix, however, that inflation may well play a role. Therefore, yet another econometric version of Eq. 2 needs to be considered:

$$p_t + \delta_3 \Delta p_t + \delta_2 w_t + \delta_1 t + \delta_0 = \varepsilon_t. \tag{7}$$

3.1 Data and data properties

Prior to running a straightforward regression of Eq. 7 we report the choice of the data and investigate their time series properties. The prices will be represented by the seasonally adjusted chain index deflator of the gross domestic product at factor costs and excluding housing and public service prices. Wages are paid to workers and white collar employees excluding the self-employed. For both variables we use indexes. The deflator is calculated on a quarterly basis while wages are reported once a year by the Swiss Federal Office of Statistics. In order to obtain quarterly figures, the Swiss Institute for Business Cycle Research (KOF) at the Swiss Federal Institute of Technology Zurich (ETHZ) uses a linear interpolation. A graphical impression of w_t and p_t is provided in Fig. 1.

Unit root tests, albeit not fully consistent with one another, indicate that prices and wages may be driven by stochastic trends with an order of integration of two, denoted $I(2)$. Therefore, in the following a multivariate cointegration framework is used that is capable of $I(2)$ stochastic trends.[2]

[2] Refer to Table 4 in the Appendix for details of the test statistics.

3.2 Economic and econometric hypotheses

Using the notation $I(d)$ to indicate integration of degree d we state the following hypotheses about the properties of coefficients and terms in Eq. 3. Throughout we make use of the assumptions that η_t is stationary ($I(0)$).

No.	Hypothesis	Interpretation
$\mathcal{H}_0^1$	$\delta_2 < 0,\ \delta_1 > 0$	Price equation holds
$\mathcal{H}_0^2$	$\mathcal{H}_0^1 \wedge \varepsilon_t \sim I(0) \wedge \delta_3 = 0$	Trend stationary technical progress
$\mathcal{H}_0^3$	$\mathcal{H}_0^1 \wedge \varepsilon_t \sim I(1)$	First difference stationary technical progress
$\mathcal{H}_0^4$	$\mathcal{H}_0^1 \wedge \varepsilon_t \sim I(2)$	Second difference stationary technical progress
$\mathcal{H}_0^5$	$\mathcal{H}_0^2 \wedge \varepsilon_t \sim I(0) \wedge \delta_3 \neq 0$	Markup and inflation are cointegrated

The above scheme makes use of the proposition that the markup can be accounted for by either supply shocks (changes in labour productivity ≡ technical progress) or demand shocks. Very often, the markup is simply understood as varying without making reference to particular reasons, see e.g. Banerjee et al. (2001). The analysis naturally focuses on $\mathcal{H}_0^1$, although the choice of the estimation technique depends on $\mathcal{H}_0^2$ to $\mathcal{H}_0^4$. As noticed before, ε_t is the sum of shocks to the technical progress and to the elasticity of goods demand. In general, it will be impossible to disentangle these two. Therefore, instead of assuming a stationary shape of the demand curve, a random-walk-like behaviour could be considered. In fact, even linear combinations of $I(2)$ demand and productivity shocks could be supposed which are either $I(0)$, $I(1)$ or $I(2)$. Furthermore, Banerjee et al. (2001) using Australian data find that the $I(1)$ markup cointegrates with inflation to a stationary variable. The corresponding precondition for that is hypothesis $\mathcal{H}_0^5$ here.

3.3 System cointegration analysis

The estimation of Eq. 3 will now be set in a multivariate time series model. We follow Rahbek et al. (1999) who provide an asymptotic theory for the Johansen (1992) two-step approach with trending variables. The empirical model reads

$$
\begin{aligned}
y_t &= (p_t, w_t)' \\
y_t^* &= (y_t', t)' \\
\Delta^2 y_t &= \Pi y_{t-1}^* + \Gamma \Delta y_{t-1} + \sum_{i=1}^{p-2} \Gamma_i \Delta^2 y_{t-i} + \mu_0 + \mu_1 t + u_t \\
\Pi &= \alpha\beta' \\
\alpha_\perp' \Gamma \beta_\perp &= \xi\nu'
\end{aligned}
\tag{8}
$$

where α and β are $(n \times r)$, $r \leq n$ matrices of full column rank, with n denoting the dimension of the process. Likewise ξ and ν are $((n-r)\times s)$ matrices of full column rank with $s < n-r$. We define the $(n\times m)$ matrix $\kappa_\perp$ as the orthogonal complement to κ $(n\times m)$ with $\kappa_\perp{}'\kappa = 0_{m\times m}$. Finally, Γ_i are coefficient matrices, μ_0 and μ_1 account for trends and ensure that the vector of innovations, u_t has zero mean. It is assumed that μ_0 and μ_1 are restricted such that at most linear trends in y_t are present (see p. 267 in Rahbek et al. 1999).

We can now relate the hypotheses formulated in Section 3.2 to r and $n-r-s$ as follows.

No.	Hypothesis	Interpretation	$r, n-r-s$
$\mathcal{H}_0^1$	$a_1 > 0,\ \delta_1 > 0$	Price equation holds	1, 1 or 1, 0
$\mathcal{H}_0^2$	$\mathcal{H}_0^1 \wedge \varepsilon_t \sim I(0) \wedge \delta_3 = 0$	Trend stationary technical progress	1, 1 or 1, 0
$\mathcal{H}_0^3$	$\mathcal{H}_0^1 \wedge \varepsilon_t \sim I(1)$	First different stationary technical progress	0, 1 or 0, 0
$\mathcal{H}_0^4$	$\mathcal{H}_0^1 \wedge \varepsilon_t \sim I(2)$	Second different stationary technical progress	0, 2
$\mathcal{H}_0^5$	$\mathcal{H}_0^2 \wedge \varepsilon_t \sim I(0) \wedge \delta_3 \neq 0$	Markup and inflation are cointegrated	1, 1 or 1, 0

It may be noteworthy that the sets of r and $n-r-s$ are not unique for each hypothesis (see last column). They are, however, unique across lines two to four. All these hypotheses except $\mathcal{H}_0^5$ can be tested in the framework of Rahbek et al. (1999) and the choice of r and s will determine the way the parameters in Eq. 10 are going to be estimated. Table 1 reports the results. The tests are based on Eq. 8 with $p=6$ being chosen according to the Akaike information criterion. The seemingly

Table 1 Hypotheses tests about the cointegration rank

Model 8 with $p=6$, sample period: 1982q4 – 2002q4						
	Basic model			*D83q3* included		
Cointegration test						
r	$S(r, s)$		$Q(r)$	$S(r, s)$		$Q(r)$
0	60.38	36.44	31.94	52.65	32.28	27.59
	47.60	*34.36*	*25.43*	–	–	–
1	–	**14.02**	7.30	–	11.99	3.72
	–	*19.87*	*12.49*	–	–	–
$n-r-s$	2	1	0	2	1	0
Specification analysis for Eq. 8 with $r=s=0$, $p=6$						
Log-lik	738.572		–	744.979		–
Portm 9	24.30		–	25.10		–
AR 1–5	$F(20, 112)=1.87$ [0.02]			$F(20, 110)=0.90$ [0.59]		
Normality	$\chi^2(4)=13.30$ [0.01]			$\chi^2(4)=15.12$ [0.00]		
Hetero	$F(78, 114)=0.80$ [0.85]			$F(78, 111)=0.52$ [0.99]		

D83q3 is short for impulse dummy (third quarter of 1983) included as an unrestricted variable in Eq. 8

Estimation for the model with $r=s=0$ is performed with *PcGive10.0*

Upper part: the 5% critical values (if applicable) are given in italics below the test statistics (see Table 1 of Rahbek et al. 1999). Statistics are calculated with Clara Jørgensen's procedure for *Cats in Rats* (see Rahbek et al. 1999)

Lower part: the specification test are based on residual vector analysis and regard the log-likelihood value ('log-lik'), presence of autocorrelation (Portmanteau test for nine lags, 'Portm 9' and F-test, 'AR 1–5'), normality (χ^2 -test, 'Normality') as well as heteroscedasticity (F-test, 'Hetero') of the residual distribution. Marginal significance levels are given in brackets if available and degrees of freedom in parentheses large lag order might be considered a result of the linear interpolation of the wage data series. A plot of the residual indicates an outlier at 1983 third quarter which is accounted for by a dummy variable in an alternative analysis. The testing procedure reported in Table 1 is a sequential one which can be read from left to right and top to bottom. Each of the entries represents a hypothesis about the process 8. For example, in the top left corner (upper part of Table 1, basic model) it is assumed that $r=0$ and $n-r-s=2$ which implies that Π and Γ are both zero and hence no long-run restrictions are imposed on the variables. This is a more general model than the one defined by the hypothesis next to the right: $r=0$ and $n-r-s=1$, and so on. It might be worth noting that the last column refers to a system with only $I(1)$ variables in y_t. The sequence of tests stops when the hypothesis cannot be rejected for the first time. The asymptotic 0.05 critical value for each hypothesis can be found below the test statistics if available.

According to Table 1 the sequence ceases at the hypothesis $\mathcal{H}_0^2 : r = 1$, $n-r-s=1$, and hence $s=0$. This result corresponds to the following first largest four eigenvalues of the companion matrix of Eq. 8 (at $p=6$, $r=s=0$): 0.9768, 0.9557, 0.9557, 0.78 of which the first two are not found to deviate significantly from one.[3] Considering the third eigenvalue as one, would imply that there is no cointegration ($r=0$), accepting only one unit eigenvalue would render the system $I(1)$. The experiences with sequential system cointegration tests for $I(1)$ models show that very often there is a power problem implying that the test procedure stops 'too early' (too low a r is chosen) if p is relatively large. Likewise, accounting for outliers (see the right hand side columns in the upper part of Table 1 labelled $D83q3$) by the inclusion of dummies may further reduce the power of the test which also implies that the test sequence stops 'too early'. Augmenting this finding to the $I(2)$ case by analogy, it seems justified to summarize the evidence by regarding $r=1$ and $s=0$ an acceptable description of the data generating process. Based on the comparison of the log-likelihood values for the model alternatives with and without dummy variable, we maintain the dummy in all the following analysis.

Putting it less technically, the tests show that one linear combination of the endogenous variables in levels and in first differences (as well as a time trend) exists which is stationary ($I(0)$). In general, this linear combination is a so-called polynomial cointegration relationship between a linear combination of the endogenous variables in levels and a combination of the endogenous variables in first differences. The most prominent candidate for such a polynomial cointegration relation is a relation between $p_t+\delta_2 w_t+\delta_1 t+\delta_0$ and Δp_t which underlines the role δ_3.

Under $\mathcal{H}_0^2$ and at $p=6$ the estimates are: $\widehat{\delta}_1 = .0032$, $\widehat{\delta}_2 = -1.152$ (estimates of coefficients and variables are indicated by ˆ).[4] We can now put forth further hypotheses about the coefficients and thereby confirm their statistical significance.

[3] This result is relatively robust with respect to the variation of p. For $3\leq p\leq 6$ the largest eigenvalue is always larger than 0.95, the second and third largest are above 0.9, and the fourth does not exceed 0.78. At $p=7$ the four largest eigenvalues are 0.9266, 0.9266, 0.88, 0.88.

[4] An anonymous referee has pointed out that $\widehat{\delta}_1$ implies an annual productivity growth rate of 1.25% which approximately matches the observed sample period's average annual productivity growth rate.

For example, $\mathcal{H}_0^5$: $\delta_2 = -1$ (linear homogeneity) and $\mathcal{H}_0^6$: $\delta_1 = 0$ (zero log-linear productivity growth) have been tested to the effect that both hypotheses individually and jointly had to be rejected at the 0.00 level of significance. At the same time $\mathcal{H}_0^1$ cannot be rejected.

The estimation of δ_3 is a bit more involved. Before turning to this issue we note that the polynomial cointegration relation can be written as

$$\beta' y_t^* + \gamma\beta_\perp \Delta y_t^* \tag{9}$$

where γ is a scalar and the representation follows from $r = 1$, $n = 2$ and $\alpha_\perp' \Gamma\beta_\perp = 0$ (see Section 4.3 in Johansen 1995). Thus, we can state the intermediate result. Under $\mathcal{H}_0^2$ the following is a stationary relationship[5]

$$\hat{\varepsilon}_t^* = p_t - 1.152w_t + .0032t + \gamma(.933\Delta p_t + .810\Delta w_t) + \delta_0. \tag{10}$$

We now confirm that $\gamma \neq 0$ by noting that $\beta' y_t^*$ is not integrated of degree higher than 1 and $\beta_\perp \Delta y_t^*$ cannot be $I(0)$. In line with Kongsted (2005), Johansen and Lütkepohl (2005) we can consider the following autoregressive model in the $I(1)$ space

$$\Delta X_t = \tilde{\alpha}\tilde{\beta}' X_{t-1} + \sum_{i=1}^{p-2} \tilde{\Gamma}_i \Delta X_{t-i} + \Phi Z_t + \tilde{u}_t \tag{11}$$

with $X_t = \begin{pmatrix} X_{1,t} \\ X_{2,t} \end{pmatrix} = \begin{pmatrix} \beta' y_t^* \\ \beta_\perp' \Delta y_t^* \end{pmatrix}$, $\tilde{u}_t = \begin{pmatrix} \beta' u_{1,t} \\ \beta_\perp' u_{2,t} \end{pmatrix}$ and where $\tilde{\beta} = \begin{pmatrix} 1 \\ \gamma \end{pmatrix}$ is the parameter vector of interest. The vector Z_t is a vector with exogenous variables. For the time being $D83q3$ is its only component. We replace β and $\beta_\perp$ in Eq. 11 by their estimates and first test for cointegration.[6] If the variables in Eq. 8 were really $I(2)$ we would expect the rank of $\tilde{\beta}$ to be exactly 1 in Eq. 11. However, in line with the assumption that the variables in y_t contain $I(2)$ components, the appropriate null hypothesis has to consider the possibility that the $I(2)$ to $I(1)$ transformation may have gone fail. Therefore, the cointegration analysis is based on a model like Eq. 8 with X_t and X_{t-1} being used instead of y_t and y_{t-1}^* respectively. The test results are provided in Table 2. At the 5% level of significance the order of integration is 1 with one cointegrating vector being present. Including a dummy and using the same table of critical value the same result is obtained at the 10% level. This result leaves two possibilities. Either $\gamma = 0$ and, hence $\beta' y_t^* \sim I(0)$ or, $\gamma \neq 0$ and $\beta' y_t^*$ would be cointegrating with $\beta_\perp \Delta y_t^*$ to a stationary process.

As Johansen and Lütkepohl (2005) note, the hypothesis $\gamma = 0$ can be tested within model 11 as a hypothesis on $\tilde{\beta}$ if β was known. The corresponding likelihood-ratio-statistic would be χ^2 distributed with one degree of freedom. In our case β is estimated, however. The likelihood-ratio-statistic may therefore not follow the χ^2 distribution exactly.[7] It can be argued, however, that due to the fact

[5] The estimation is performed with *Cats in Rats*.
[6] Summary statistics for residual properties are provided in Table 3.
[7] I am indebted to an anonymous referee for valuable advise on the issue.

Table 2 Hypotheses tests about the cointegration rank for X_t

Model 8, y_t=X_t, y^*_{t-1}=X_{t-1}, p=6,						
Sample period: 1982q4–2002q4						
	Basic model			*D83q3* included		
r	$S(r, s)$		Q(r)	S(r, s)		$Q(r)$
0	84.46	52.91	31.76	80.88	48.18	31.43
	36.12	*26.00*	*19.96*	–	–	–
1	–	20.30	**6.23**	–	12.05	6.50
		12.93	*9.24*	–		–
$n{-}r{-}s$	2	1	0	2	1	0

D83q3 is short for impulse dummy (third quarter of 1983) included as an unrestricted variable in Eq. 8. Estimation for the model with r=s=0 is performed with *PcGive10.0*. The 5% critical values in italics below the test statistics (if applicable) are from Paruolo (1996), Table 5

that the evidence as of Table 2 points to a valid $I(2)$ to $I(1)$ transformation and presence of a cointegrating relation in X_t, the corresponding cointegration parameter (γ) will be superconsistently estimated and hence χ^2 distribution applies asymptotically. The empirical test statistics is found to be 14.55 and thus the hypothesis $\gamma=0$ can be rejected under the conditions mentioned before. Moreover, since the property of cointegration is not lost when replacing $\beta_{\perp}\Delta y^*_t$ by Δp_t we are able to calculate $\hat{\delta}_3$ from the estimate for γ in Eq. 11. We obtain $\hat{\gamma}=-1.19$ (standard error: 0.2). Considering further that $\Delta p_t-(1.152\Delta w_t)\sim I(0)$ and therefore, in the long-run $\Delta w_t=1/1.152\Delta p_t$ leads to $\hat{\delta}_3=-1.95$. Thus, $\mathcal{H}^0_5$ finally finds support and we have

$$\hat{\varepsilon}_t = p_t - 1.152w_t + .0032t - 1.95\Delta p_t + .468. \tag{12}$$

This relationship will be considered the empirical, inflation adjusted markup-relationship, while

$$\widehat{mu_t} = p_t - 1.152w_t + .0032t \tag{13}$$

will be called the markup-relationship and considered $I(1)$. Finally, for mainly expositional reasons we also define

$$\hat{\varepsilon}^*_t = p_t - 1.152w_t + .0032t - 1.19 \times (.933\Delta p_t + .810\Delta w_t) + .468. \tag{14}$$

as the price and wage inflation adjusted markup relation. It might be worth noting that Eq. 12 implies a positive relation between the markup and inflation. This is a finding that does not correspond to the findings by e.g. Banerjee et al. (2001, 2002), and Banerjee and Russell (2000) who also rule out this possibility altogether on theoretical grounds. In contrast, however, to their approach the relation between markup and inflation is not motivated by considering costs of inflation rather than by optimal behaviour under uncertainty. That's why, the actual relation depends on the properties of the demand for goods and may result in a positive, negative or zero correlation between markup and inflation. However, owed to the lack of truly comparable data, a comparison to the aforementioned results could only be made on very weak basis.

4 Semantic cross validation

In Eq. 12 we obtained an estimate for the time varying part of the inflation adjusted markup on marginal costs. It has been argued before, that this measure should follow business cycle fluctuations caused by demand and labour productivity variation. Due to the fact that economic theory underlies Eq. 12 we can argue that $\hat{\varepsilon}_t$ represents a business cycle indicator obtained by economic filtering as opposed to (purely) technical filters like HP-filter or structural time series analysis. The indicator $\hat{\varepsilon}_t$ can also be seen as an application of Granger and Jeon's (2003) time–distance measure. It should furthermore be pointed out that such an indicator has the advantage that its numerical values can directly be associated with precise statements about the expected reaction of the economy. Technically derived indicators do not have this kind of 'natural' interpretation. Moreover, providing quantitative statements does not necessarily depend on the identifiability of the components of the indicator like demand and supply shock as in our case.

Summarising the arguments one could regard the economic filter as an example where the measure's *implication* has a specific semantic content while the *reason* for the effect may be largely unknown due to the infinite universe of interpretations which one might attach to $\hat{\varepsilon}_t$. There exists, however, another class of information where the situation is more or less the opposite. This class is business tendency survey data (BTS data). This data is generated by means of specific semantic questions. For example, respondents may be asked if they expect lower, equal, or higher inflation in the next period. After appropriate aggregation of the answers this information could be used as information about inflation expectations. It can be supposed that the semantic content of this data is known. What is not known, however, is the implications for the economy.

As a consequence of the above considerations, this paper uses independent information from both sources as complements. Taken together they should provide a consistent picture with additional insight none of them could generate alone. Looking from the perspective of the economic filter, a comparison to BTS data should shed light on the identification problem. On the other hand, the BTS data can be assessed not only by means of its nominal semantic content but also by what it implies in terms of the economy's development. This comparison of two independently generated information sets with a common semantic basis shall be called semantic cross validation; an example of which is given in the following.

The KOF conducts a large number of surveys in Switzerland which attempt to give a reliable picture of the economy. In order to facilitate semantic cross validation we should look for information about (unexpected) marginal cost and demand fluctuations. Two principal methods to identify such data could be thought of. The first could be a regression or correlation analysis of $\hat{\varepsilon}_t$ and potential data where the series with the largest correlation or explanatory power could then be considered. The preferred alternative naturally seems to be a look at the semantics of the survey questions. Following Stalder (1994) we pick the responses to the inquiry about capacity constraints in the industry. At a later stage of this project, further series are going to be scrutinised in the same way.

The capacity question inquires whether firms' technical capacities are too low, sufficient, or too high. Naturally, in the absence of shocks, technical capacities will always be chosen such that firms supply the(ir) optimal equilibrium amount. If this is not the case firms are facing a shock requiring them to adjust capacities in the aftermath. The difference between firms reporting too high and too low capacities can thus be used to approximate the state of the business cycle in the sense that shocks push firms away from their point of optimal capacity utilisation. Since the production technology and hence costs of production is private information, inappropriate capacities should be due to exogenous factors, the most important being demand shocks. This variable, denoted π_t, will be compared to $\hat{\varepsilon}_t$ in the following.

First, a unit root analysis is conducted for π_t. If π_t and $\hat{\varepsilon}_t$ are ought to be similar, π_t should feature mean reverting behaviour and finite variance as does $\hat{\varepsilon}_t$. Strictly speaking, the survey data should be stationary by definition, therefore, the statistical test is not really necessary. It is nevertheless conducted and supports the stationarity hypothesis (test statistics are reported in Table 4). Second, plotting these two variables adjusted for their means and variances, reveals that they both are strikingly similar in their evolution over time. This can be confirmed from Fig. 2.

A statistical analysis shows that the correlation between π_t and $\hat{\varepsilon}_t$ is 0.31 while it is 0.34 between π_t and $\hat{\varepsilon}_t^*$. Furthermore, a formal OLS regression of $\hat{\varepsilon}_t\left(\hat{\varepsilon}_t^*\right)$ on π_t and a constant shows a significant linear relationship. The corresponding *t*-value of the coefficient on π_t is 2.03 (2.15) when corrected for heteroscedasticity and autocorrelation of the residuals. That's why one can conclude that there is enough evidence to reject the hypothesis that $\hat{\varepsilon}_t\left(\hat{\varepsilon}_t^*\right)$ and π_t to a significant extent do not represent the same information.

In the following, the residual series corresponding to the regression of $\hat{\varepsilon}_t^*$ on π_t and a constant is going to be called $\hat{\varepsilon}_{\pi,t}^*$. We define a π_t^* which obeys to $\pi_t^* = \hat{\varepsilon}_t - \hat{\varepsilon}_{\pi,t}^*$ and has the useful property to be uncorrelated with $\hat{\varepsilon}_{\pi,t}^*$ but to preserve all necessary information about π_t.[8]

The results of the cross validation exercise imply that a significant part of the variance in $\hat{\varepsilon}_t$ originates in demand shocks. On the other hand, the model provides a tool for directly assessing the numerical relevance of the particular BTS data with respect to wages and prices.

4.1 The business cycle, technology shocks, and dynamics of markup pricing

The following section tries to push the previous cross validation approach a bit further by addressing two identification issues. The first deals with the possibility to differentiate between demand shocks and technology shocks, the second looks at

[8] Analytically, it does not matter whether we use $\hat{\varepsilon}_t$ or $\hat{\varepsilon}_t^*$ although $\hat{\varepsilon}_t$ is easier to interpret economically. The following computations are nevertheless based on $\hat{\varepsilon}_t^*$ because it meant less programming effort.

the response of the Swiss economy to a shock in order to confirm markup pricing power.

4.1.1 Technology shocks

It has been found that the information content of $\hat{\varepsilon}_t^*$ and π_t is very similar. In addition to the similarity, the differences might also be noteworthy. Having in mind that the firms' answers relate private decisions to the public demand for its goods, it is a relation between endogenous and exogenous factors. The endogenous part encompasses all parameters the firms can choose themselves subject to given exogenous factors like the demand function and expectations about demand for goods. The firms' decision is the level of output (and hence prices) which is of course closely related to the choice of inputs. This choice is in turn made subject to the production function which is private information. The key argument here is that while on a macro level the production function is a black box, it is not so at the firm level. The production function naturally depends on the technology used and hence determines labour productivity. Therefore, when answering the survey, firms can be expected to accommodate technological shocks that have affected their production function. This is because even if a new shock arrives, on the firm level this innovation would first have to be implemented which implies that it enters the decision and expectation-making process before the output level is chosen. Consequently, π_t should almost exclusively convey information about demand shocks, the only major source of surprise for the firm. Thus, the informational difference between $\hat{\varepsilon}_t^*$ and π_t might largely be attributed to technology shocks affecting labour productivity. Of course, to the extent that $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are correlated, π_t is also informative about shocks to marginal costs, but an exact differentiation appears unnecessary to the same extent.

4.1.2 The dynamics of markup pricing

So far, it had been shown that there is a linear relationship between prices, wages, and a time trend that is following business cycle fluctuations. What is left though, is to show that this indicator indeed equips firms with additional or reduced power to raise prices. This, however, can easily be confirmed by checking that the coefficients of $\hat{\alpha}$ in Eq. 8 corresponding to the price equation are significant and have the correct sign. Based on Eq. 8 and imposing the restrictions 14 we obtain $\widehat{\alpha} = \begin{pmatrix} 0.043 \\ 0.111 \end{pmatrix}$. A likelihood ratio test confirms that the element of $\hat{\alpha}$ corresponding to the equation for $\Delta^2 p_t$ is statistically significant. The χ^2-statistic with one degree of freedom amounts to 19.71.[9]

The basic consideration is that in complete markets firms would be price takers and always supply at their marginal cost. In short, demand shocks would not affect the price level while technology shocks would.

[9] The computation is performed with *Cats in Rats*.

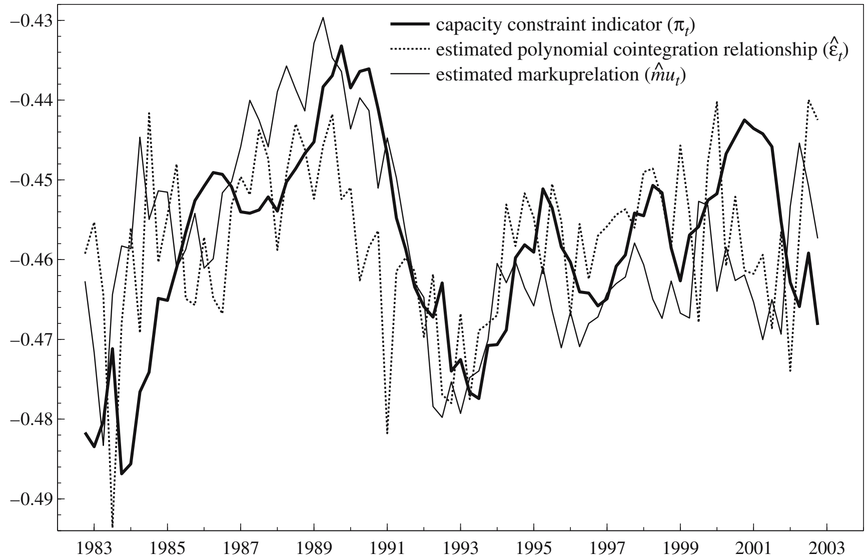

Fig. 2 Graphical semantic cross validation

Figure 3 shows hypotheses about the potential dynamics in the stylized economy. The reference point is A which corresponds to the optimal choice of the firm given shape and position of the demand curve ($\overline{DD}$) and the production technology (and hence marginal costs). If demand would be higher due to larger consumer budget, for example, this would be signified by an outward shift of the demand curve to $\overline{D'D'}$. The new optimal point would be A' and the points along this expansion line define the supply curve $\overline{SS}$. For a given period of time, A is optimal only if it is a point on the demand curve. The position of the latter, however, is not known with certainty. It can only be considered to be the expected demand from the viewpoint of the firms. The true position will be revealed when the products are put on the market. For convenience, the situation of a positive

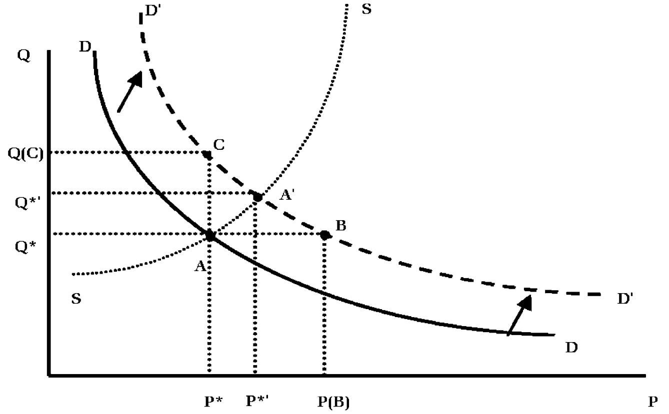

Fig. 3 Price-quantity adjustment after a positive demand shock

demand shock will be considered. A negative shock would simply lead to opposite conclusions. Such a shock is equivalent to a statement of too low capacities compared to demand. Therefore, the realised demand is $\overline{D'D'}$ and the desired optimal point is A'. However, in the short run it might not be possible to jump to A' directly because of capacity constraints or difficulties in adjusting prices. Thus, B and C are extreme initial positions at the time of the shock where either only prices (B) or quantities (C) are changed to arrive at $\overline{D'D'}$.

According to the previous discussion, two adjustment paths are possible. Either $\overrightarrow{BA'}$ or $\overrightarrow{CA'}$. The first would imply that after a positive shock the firms initially choose too high prices compared to the optimal A'. Therefore, a downward pressure on prices has to follow the initial reaction. If output would be increased instead (point C), then prices would rise in the aftermath of the shock. The simple test therefore is a look at the adjustment path.

Restricted reduced form estimation The adjustment path will be given as an impulse–response analysis of a temporary demand shock to Eq. 11 in conjunction with Eq. 14. To this end, the immediate impact of a demand shock needs to be accounted for and we have to separate the effect on $\widehat{\varepsilon}_t^*$ into demand related and all other effects. Two simple modifications help to distinguish the effects.

We first add $\Delta\pi_t$ and π_{t-1}^* to the vector Z_t. In this step, only $\Delta\pi_t$ provides additional, original information since $\tilde{\beta}' X_{t-1}$ already accounts for a significant share of the variation in π_{t-i}^*. Second, in order to truly identify the effects due to π_t in Eq. 11, $\tilde{\beta}' X_{t-1}$ is replaced by $\hat{\varepsilon}_{\pi,t-1}^*$. Table 3 (right hand part) has the details of the corresponding summary model evaluation. The overall properties appear satisfactory, although there is some indication of non-normality of the residuals.

It is now easy to apply a temporary shock to π_t and to observe the responses that are triggered in p_t and w_t.[10]

A plot of the impulse–responses is given in Fig. 4. We report the effect on the first 24 quarters, that is, for the first 6 years after the shock. The scale of the responses is linear in the shocks, hence arbitrary and therefore not given. Unfortunately, we are not able to say anything about the significance of the effects. Therefore, the following has to be conditioned on the hypothesis that the true responses are not zero. Note, however, that a simple test about the significance of the information contained in π_t is feasible by testing the joint significance of the parameters corresponding to $\Delta\pi_t$ and π_{t-1}^*In the more general restricted reduced form model reported in Table 3 (right hand part) the α correspond to $\widehat{\varepsilon}_{\pi,t-1}^*$ yet not to $\tilde{\beta}' X_{t-1}$ as in the model reported in the left hand side. Therefore, the null hypothesis of the survey data being not important in the data generating process leads to a model that is more restrictive than simply switching off the coefficients for $\Delta\pi_t$ and π_{t-1}^* in Z_t, and hence more restrictive than the model reported on the left hand side of Table 3.

The corresponding likelihood-ratio statistic with four degrees of freedom amounts to 8.54 with 0.07 as the p value. A test on the significance of π_{t-1}^* alone

[10] Technically, the model is estimated by *full information maximum likelihood* with identity equations added for π_t, $\widehat{\varepsilon}_t^*$, π_t^*, Δp_t, p_t, Δw_t and w_t and then a once-off shock is given to the equation for π_t^* or $\widehat{\varepsilon}_t^*$, respectively.

Table 3 Summary statistics for restricted reduced form analyses

Model 11 and 14 with $p = 6$, sample period: 1982q4 – 2002q4		
	$Z_t = D83q3'$	$Z_t = (D83q3,\ \pi^*_{t-i},\ \Delta\pi_t)'$
Log-lik	677.656	679.701
Portm 9	34.96	35.63
AR 1–5	$F(20,\ 128) = 1.25$ [0.22]	$F(20,\ 124) = 1.93$ [0.27]
Normality	$\chi^2(4) = 8.14$ [0.09]	$\chi^2(4) = 12.17$ [0.02]
Hetero	$F(105,\ 111) = 1.21$ [0.16]	$F(108,\ 102) = 1.18$ [0.20]

The results in the right part of the table refer to a model as in Eq. 11. However, $\tilde{\beta}' X_{t-1}$ is replaced by $\hat{\varepsilon}^*_{t,\pi}$. The details are explained in the main text. Estimation is performed with *PcGive10.0*. See Table 1 for further explanations

gives $\chi^2(2) = 6.94$ having p value 0.03. It is therefore justified to consider the more general model to be more appropriate than a model that completely disregards the information provided by π_t.

One might first look at the response of the endogenous variables to a temporary positive change in the long-run equilibrium. It causes an increase in prices as well as in wages which (bottom panels), however, is of a temporary nature. At the end of the 6 years, a new price level is reached. Such a shock is, of course, hard to interpret since it does reflect the effect of anything that may disturb the long-run equilibrium without allowing a demand shock also to hit the system in the initial period. It does, however, illustrate the equilibrium correction behaviour of the long-run equilibrium model.

Contrary to this shock, a pure demand shock has an effect which is consistent with a jump from A to B (c.f. Fig. 3) in the initial period. This can be seen in the

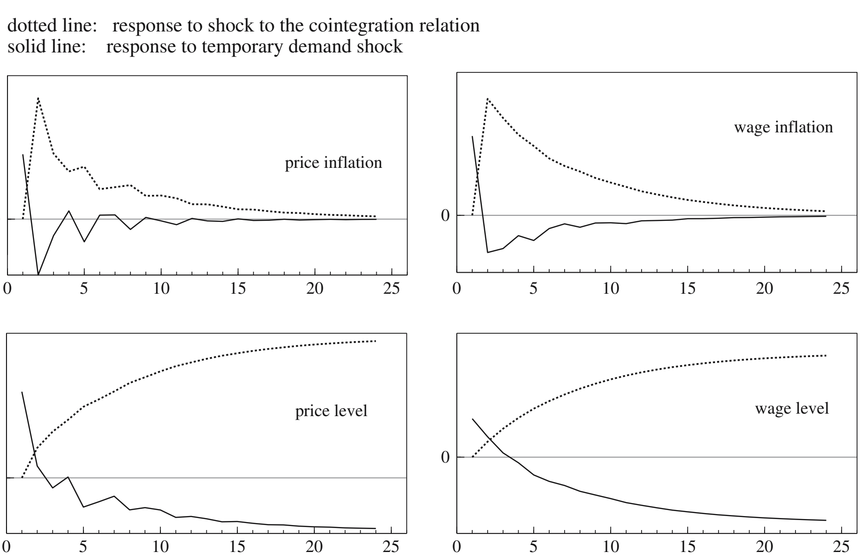

Fig. 4 Impulse–responses to a shock to demand and to the inflation adjusted markup relation($\hat{\varepsilon}^*_t$, c.f. Eq. 14)

bottom left panel of Fig. 4, where the price level jumps up in the period at which the shock occurs. During the remaining periods the price level declines at declining speed (see top left panel), which mimics a move from B to A' and finally back to A in Fig. 3 since the shock has temporary effects only. In our example the final price level is below the initial one because we are estimating the model in the price-wage-space rather than in the price-quantity-space. The model supposes wages to be exogenous while in fact in the empirical application it is also endogenous. Therefore, unless we restrict the final wage level to match the initial one, we cannot expect the long-run value of the price level in the aftermath of the temporary shock to coincide with the original price level.

5 Summary and outlook

This paper has suggested a semantic cross validation procedure that provides the opportunity to complement economic analysis with business survey data sources. It furthermore helped to address the identification problem and offered the possibility for quantifiable interpretation of qualitative data.

The procedure has been demonstrated in a small macroeconomic model where it has been shown that firms might have time varying power to conduct markup pricing. This opportunity was attributed to the possibility of unexpected changes in the strategic position of firms for optimal price setting. For example, firms could be faced with a shift of the demand curve due to unpredicted events.

These results could be used for further research into - among other - the following directions. The implicit measure of technological shocks could further be scrutinised by comparison with more direct measure of innovations obtained by survey data itself. Furthermore, since the demand shock indicator is a so-called balance variable reporting the difference between the share of firms having excess and too few capacities, it could be supposed that positive and negative demand shocks may have different effects. Therefore, a more detailed investigation into this aspect might be desirable.

Second, under the assumption that the principal source for variations in $\hat{\varepsilon}_t$ are shifts of the demand curve while the shape of the curve remains constant, one could engage in estimating the demand curve in the price-quantity space. This would e.g. require to extend the model in order to incorporate GDP income.

Finally, since the error correction term can be interpreted as a business cycle indicator, the BTS data which is very closely related to this information set could well be used as a business cycle indicator itself. Therefore, using BTS data in that way would even have an edge over the approach by Granger and Jeon (2003) who use observed disequilibrium errors which are available with a time lag only. Furthermore, the BTS based indicator would not be subject to revisions and it would in contrast to technical approaches not be dependent on assumptions about the data generating process of, e.g. GDP. It would however, be dependent on the supposed economic theory which in turn can in many cases be empirically rejected or supported.

Appendix

An extension of the basic economic model

We need to show that inflation can be linked to the markup. Define $P_t = \omega P_t^m + (1-\omega) P_t^c$ with $0 \le \omega \le 1$ and P_t^m, P_t^c are the prices in the monopolistic and the perfect competition sector of the economy, respectively. The procedure is as follows. It will be shown that the demand elasticity in the monopolistic sector is affected by changes in P_t^c. By assumption the firms in the competitive sector are price takers and hence are not affected by P_t^m.[11] Then, given that the same absolute change in the elasticity has a different impact on profits depending on the sign of the change, it is argued that the expected profit is maximised by choosing a price level that deviates from the one given in Eq. 2. Thus, the first and second derivatives of profits with respect to the demand elasticity need to be calculated and the two situations, one positive and the other with negative expectation errors are to be compared to one another. Finally, since P_t is a weighted average of P_t^m and P_t^c and labour is assumed to have the same price everywhere in the economy it can be argued that the price setting behaviour of the monopolistic sector is reflected in the economy wide aggregates of prices and wages as it is done in the main text.

The demand elasticity and P_t^c

First, the behavioral equations are re-stated:

$$\begin{array}{lll}
\text{production} & Q_t = Q(L_t), & \dfrac{\partial Q}{\partial L_t} > 0, \\
\text{demand} & P_t^m = P^m\big(Q(L_t), P_t^c\big), & \dfrac{\partial P^m}{\partial L_t} = \dfrac{\partial P^m}{\partial Q}\dfrac{\partial Q}{\partial L_t}, \\
\text{inverse demand} & Q_t = Q\big(P^m\big(P_t^c\big)\big), & \dfrac{\partial Q}{\partial P_t^m} < 0, \ \dfrac{\partial Q}{\partial P_t^c} \gtrless 0, \\
\text{demand elasticity} & \eta_t = \eta\big(P_t^m, Q_t\big), & \eta_t^{-1} = \dfrac{\partial P^m}{\partial Q}\dfrac{Q_t}{P_t^m} \ \textit{with}\ \eta_t < -1.
\end{array}$$

The optimal solution conditional on P_t^c is equivalent to Eq. 2:

$$P_t^m = \left(1 + \eta_t^{-1}\right)^{-1} a_1 W_t^{a_2} \tau_t^{-a_3}, \tag{15}$$

[11] This assumption could also be dropped which would only mean a couple of more lines, yet not change the main implications.

We need to know the impact of P_t^c on η_t:

$$\eta_t = \frac{\partial Q}{\partial P^m}\frac{P_t^m}{Q_t}$$
$$= P^m(Q_t, P_t^c)\frac{\partial Q(P^m(P_t^c))}{\partial P^m(Q_t, P_t^c)Q(P^m(P_t^c))},$$

and hence,

$$\begin{aligned}
\frac{\partial \eta}{\partial P^c} &= \frac{\partial P^m\left(P_t^c\right)}{\partial P^c}\frac{\partial Q\left(P^m\left(P_t^c\right)\right)}{\partial P^m\left(Q_t, P_t^c\right)Q\left(P^m\left(P_t^c\right)\right)} + P^m\left(P_t^c\right)\frac{\partial\left(\frac{\partial Q\left(P^m\left(P_t^c\right)\right)}{\partial P^m\left(P_t^c\right)Q\left(P^m\left(P_t^c\right)\right)}\right)}{\partial P^c} \\
&= \frac{1}{Q_t}\frac{\partial P^m}{\partial P^c}\frac{\partial Q}{\partial P^m} + P^m\left(P_t^c\right)\frac{\partial\left(\frac{\partial Q\left(P^m\left(P_t^c\right)\right)}{\partial P^m\left(P_t^c\right)}\frac{1}{Q\left(P^m\left(P_t^c\right)\right)}\right)}{\partial P^c} \\
&= \frac{1}{Q_t}\left[\frac{\partial Q}{\partial P^c} + P^m\left(P_t^c\right)\frac{\partial^2 Q}{\partial P^m \partial P^c} - \frac{P^m\left(P_t^c\right)}{Q_t}\frac{\partial Q}{\partial P^m}\frac{\partial Q}{\partial P^c}\right] \\
&= \frac{1}{Q_t}\left[\frac{\partial Q}{\partial P^c} + P^m\left(P_t^c\right)\frac{\partial^2 Q}{\partial P^m \partial P^c} - \eta_t\frac{\partial Q}{\partial P^c}\right] \\
&= \frac{1}{Q_t}\left[\frac{\partial Q}{\partial P^c}(1-\eta_t) + P^m\left(P_t^c\right)\frac{\partial^2 Q}{\partial P^m \partial P^c}\right].
\end{aligned} \tag{16}$$

Profit maximisation with perfect foresight

Next, we need to show that profits negatively depend on η_t. This is fairly simple and can be confirmed in any textbook. It is nevertheless given here again for completeness of the exposition. In Eq. 2 the profit maximising price is given in terms of the elasticity. Taking first and second derivatives with respect to η_t produces:

$$\frac{\partial P^m}{\partial \eta} = \frac{1}{(1+\eta_t)^2} > 0 \tag{17}$$

$$\frac{\partial^2 P^m}{(\partial \eta)^2} = \frac{-2}{(1+\eta_t)^3} > 0 \tag{18}$$

due to $\eta_t < -1$. This result does not change when we are looking at the variables in logs and therefore, the arguments hold also for the log–linear econometric model.

Maximising expected profit

After aggregating the results 16–18 we can evaluate what firms do when they do not know the realisation of P_t^c at the time they are planning production for the period t. Naturally, firms will formulate expectations at $t-1$ conditional on the information set I_{t-1} about P_t^c which we denote $E_{t-1}(P_t^c)$. Based on this value, the optimal price setting is given by Eq. 2. However, even if $E_{t-1}\,(P_t^c - E_{t-1}(P_t^c)) = 0$, firms have an incentive to deviate from Eq. 2 if the variance of the expectation error, is sufficiently large. To see this, notice that in the neighborhood of the optimal price according to Eq. 2 changes in the elasticity will have asymmetric effects on the profits. When demand becomes less elastic ($\Delta\eta_t > 0$), then profits will rise more than they would fall if demand would turn more elastic by the same absolute value. From Eq. 16 we know that deviations of P_t^c from its expected value can be regarded as expectation errors of η_t which we denote by ϱ_t. Therefore, applying Eq. 18 and using a second order Taylor approximation of P^m around $\varrho_t = 0$ gives rise to

$$P^m(\varrho_t) = P^m(E_{t-1}(\eta_t)) + \frac{\partial P^m}{\partial \eta}\varrho_t + \frac{1}{2}\frac{\partial^2 P^m}{(\partial \eta)^2}\varrho_t^2.$$

After taking expectations we obtain

$$\begin{aligned} E_{t-1}(P^m(\varrho_t)) &= P^m(E_{t-1}(\eta_t)) + \frac{\partial P^m}{\partial \eta}E_{t-1}(\varrho_t) + \frac{1}{2}\frac{\partial^2 P^m}{(\partial \eta)^2}E_{t-1}\left(\varrho_t^2\right) \\ &= P^m(E_{t-1}(\eta_t)) + \frac{1}{2}\frac{\partial^2 P^m}{(\partial \eta)^2}Var(\varrho_t|I_{t-1}). \end{aligned} \tag{19}$$

Thus, when considering the uncertainty about P_t^c the optimal price deviates from the solution in Eq. 2 by $\frac{1}{2}\frac{\partial^2 P^m}{(\partial \eta)^2}Var(\varrho_t|I_{t-1})$ which is according to Eq. 16 linear in the variance of P_t^c and therefore related to inflation. In other words, independent of the reasons for variations in P_t^c firms will have an incentive to set prices above the solution in Eq. 2 which further enhances inflation. The next paragraph will establish the relation between inflation and the markup.

Summary of the empirical hypotheses

From Eq. 18 follows that changes in the markup trigger changes of the price level in the same direction. Shocks to the markup may arise in P_t^c and can have a positive, a negative, or no impact on the markup as Eq. 16 implies. However, irrespective of whether P_t^c has risen or fallen and whether uncertainty is allowed for or not, the induced variation in η_t means a larger value for P_t^m than it would have been observed without a shock to P_t^c (see Eq. 19). Moreover, the larger the variation in the shock to P_t^c, and hence inflation, the larger the variance of η_t and the larger the increase in P_t^m.

There are thus two channels by which inflation and the markup are linked. The first is the variance of shocks to η_t which always leads to a rise in P_t^m. Since changes in the overall price level, namely due to changes in P_t^c may be responsible for variations in η_t inflation will again result. Taken together, this implies a positive relation between inflation and the markup.

The second channel is provided by Eq. 16. For $\frac{\partial \eta}{\partial P^c} < 0$ initial changes in the overall price level will lead to a decline in η_t and hence in P_t^m. Thus, inflationary impulses are not reinforced but muted. Naturally, for $\frac{\partial \eta}{\partial P^c} > 0$ the opposite holds.

The actual relationship between inflation and the markup, is therefore given by the relative importance of the two channels and the actual sign of $\frac{\partial \eta}{\partial P^c}$. In fact, there may be a positive relation, a negative, or no relation at all. In the empirical model these possibilities are represented by $\gamma<0$, $\gamma>0$, or $\gamma=0$, respectively. We do not engage in further scrutinising the theoretically correct sign of this value but leave it as an empirical question.

Auxiliary analyses

Table 4 Univariate unit root tests

Sample: 1982q4 – 2002q4, T = 81

Variable	Lag order			Test statistics*		
	AIC	FPE	HQ	Spec.	ADF	KPSS
w_t	6	6	6	t, 6	−0.53	**0.28**
Δw_t	5	5	1	5	−2.44	**0.59**
$\Delta^2 w_t$	9	5	0	4	**−3.04**	0.08
p_t	3	3	3	t, 3	−.33	**0.51**
Δp_t	2	2	2	2	**−3.60**	**1.08**
$\Delta^2 p_t$	2	2	1	2	**−7.68**	0.04
π_t	3	3	3	3	**−3.40**	0.21
$\Delta \pi_t$	1	1	1	2	**−4.51**	0.21
$\widehat{mu_t}$	3	3	3	3	−2.37	0.46
$\Delta \widehat{mu_t}$	2	2	2	2	**−4.80**	0.05
$\hat{X}_{2,t}$	2	2	2	2	−2.80	**1.21**
$\Delta \hat{X}_{2,t}$	1	1	1	1	**−11.60**	0.02
$\hat{\varepsilon}_t^*$	2	2	2	2	**−3.31**	0.16
$\Delta \hat{\varepsilon}_t^*$	1	1	1	1	**−11.10**	0.03
$\hat{\varepsilon}_t$	2	2	2	2	−2.00	**1.04**
$\Delta \hat{\varepsilon}_t$	1	1	1	1	**−10.89**	0.03

Significant test statistics are in bold face. The column 'spec.' reports if in addition to an intercept a time trend (t) and how many lagged endogenous variables entered the test regression. The columns headed by 'AIC', 'FPE', 'HQ' give the optimal lag lengths according to the commonly used model selection criteria Akaike information criterion, final prediction error, and Hannan–Quinn criteria, respectively. Calculations are performed with *JMulti 3.11* (see Lütkepohl and Krätzig 2004)

*'ADF' stands for the augmented Dickey–Fuller test and has 'non-stationarity' as the null. 'KPSS' signifies the test due to Kwiatkowski et al. (1992) and tests the null 'stationarity' versus 'non-stationarity'. The 5% critical values are −3.41 and −2.86 for the 'ADF' test with and without trend, respectively, (see MacKinnon 1991) and 0.146 and 0.463 for the KPSS test with and without trend, respectively (see Kwiatkowski et al. 1992)

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